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ABSTRACT

Three models of multiple regression analysis (MRA): single equation, commonality analysis, and path analysis, were applied to longitudinal data from the Pennsylvania Vocational Development Study. Variables influencing weekly income of vocational education students one year after high school graduation were examined: grade point averages (grades 7-9, and 10-12), socioeconomic status, and initial income. All models concluded that earnings of vocational graduates did not differ significantly from nonvocational graduates: furthermore, initial income was the best and only predictor of income one year after graduation. The path model also suggested that vocational education affects achievement in grades 10-12, which in turn affects initial income. While the three models yielded the same overall coefficient of determination, commonality and path models provided more information about the unique and shared variance of predictor variables. Path models, in particular, were recommended because they also reflected direct and indirect influence of all other antecedent or suppressor variables. (CP)

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A COMPARISON OF VARIOUS MRA METHODS APPLIED TO LONGITUDINAL EVALUATION STUDIES IN VOCATIONAL EDUCATION

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The research reported in the paper is based on the unpublished doctoral dissertation of Mohammad S. Mohagheghzadeh. All the tables and figures have been reproduced directly from the dissertation (Note 1).

Introduction

In an effort to study the results of the vocational education amendments of 1976, the Congress charges the National Institute of Education (NIE) with the responsibility for conducting a thorough evaluation and study of vocational education programs. In its proposed plan for conducting such a study, NIE (1977, p. 2) has determined that their research should include five different activities. The fifth activity which is directly related to this study reads as follows: "Analysis of the existing bodies of longitudinal data on educational and work experiences focused on the outcomes for participating in vocational education programs."

A review of major follow-up studies (including some of a longitudinal nature conducted during the past two decades) indicates that the primary methodology in such inquiries is various forms of multiple regression analysis (MRA) (Coleman, Campbell, Holson, McPartland, Mood, Weinfeld, and York, 1966; Cooley and Lohnes, 1968; Bachman, 1970; Katzman, 1971; Impelliterri and Kapes, 1971; Anderson and Evans, 1976; Andrisani and Nestel, 1976; and Picou and Howard, 1978).

Moss (1968) and other researchers (Kaufman, Stromsdorfer, Hu and Lee, 1967; Stromsdorfer, 1972; Abramson, 1979) have explicitly described the usefulness of MRA to evaluation and policy research in vocational education. Consistent with the general objectives found in the educational production function approach to analysis (Copa, 1971; Hanushek, 1978) these researchers view the general MRA methodology as most useful when program outcomes (such as student achievement, job placement, and income earned in the labor market) are to be linked with program inputs (such as student characteristics, instructional processes and other intervening variables). Efforts to more effectively model various intervening

variables in vocational education frameworks have led several researchers to explore applications of path analysis. In this domain of MRA application, Bane (1972), and others (Curry, Picou, Hotchkiss, Scritchfield, and Stahura, 1975; Kapes, Enderlein, and O'Reilly, 1976) have suggested that path diagrams and their corresponding ordinary least-square estimates provide an excellent opportunity to formulate and measure significant relationships appearing in longitudinal as well as cross-sectional data sets.

While the majority of the literature that links MRA with various educational quality assessment activities has focused almost exclusively on illustrating the benefits of MRA as a data analytic framework for evaluation, a small but important subset of the literature has focused on the limitations of MRA as a guide for interpreting evaluation data. For example, Werts and Linn (1969) have shown that the application of four alternate frameworks for regression analysis to the same data set can, in certain instances, yield precisely opposite results regarding the effects of school measures on learning outcomes. Moreover, in the heat of the recent national debate on the merits of compensatory education, Campbell and Erlebacker (1974) produced additional convincing evidence to illustrate exactly how regression models employed in quasi-experimental evaluations offered in the original Westinghouse/Ohio University study mistakenly made compensatory education appear harmful. In their study Campbell and Erlebacker have clearly demonstrated that not only the matching of experimental and control groups, but also the application of analysis of covariance and partial correlation procedures can produce regression artifacts in evaluation reports.

Consistent with the emerging trend in the literature to discount or, in some cases, overlook the unanticipated consequences of model selection on study findings, the intent of this inquiry was to compare and contrast three alternative approaches to utilizing MRA methodology with longitudinal data in Vocational

Education evaluation studies. These approaches are (1) Single Equation Models, (2) Commonality Analysis, and (3) Path Analysis. Following the leads suggested in the Werts and Linn (1969) and Campbell and Erlebacker (1976) investigations this inquiry is explicitly designed to answer the following specific research question: Do the actual inferences drawn from the three methods of applying MRA lead to different conclusions regarding the effects of Vocational Education programs?

For each of the three alternative MRA approaches, answers for two explicit evaluation questions are sought. This consideration is to provide an empirical basis for the actual inferences and conclusions to be drawn regarding the effects of vocational education programs.

The first evaluation question, which addresses the direct influences of student participation in vocational education on income in the labor force, is as follows: Does participation in vocational education make a difference in weekly income in dollars one year after graduation?

The second evaluation question, which acknowledges the influence of other input variables and interim results, is the following: What are the influences of the different intervening variables on the external program outcome which is the weekly income in dollars one year after graduation?

Methodology

The design constructed to answer the specific research question posed in this inquiry links the information base from a single longitudinal study with three specific MRA formulations. Implementation of the proposed design is as follows.

Information Base (Sample)

The data used in this study was originally collected as part of the longitudinal Vocational Development Study (VDS) project conducted within the Department

of Vocational Education at the Pennsylvania State University (Impelliterri and Kapes, 1971; Kapes, 1971; Kapes, Enderlein and Martin, 1974). The VDS project was conducted in cooperation with the Vocational Education Research Coordinating Unit of the Pennsylvania Department of Education. The collection of data started with the ninth graders in the Altoona School System in 1968, an approximate population of 1,200 students. The collection of information was continued for those who stayed with the Altoona School System and finished the twelfth grade and up to one year after graduation from high school. From this original population, all students for whom complete data on the desired variables were available were used. This provided a sample of 348 students. The reason for such a reduction from the original population include: (a) normal student attrition, (b) economic impracticality of administering some of the tests for the second time, and (c) one year follow up data available on only 781 of which some went on to college as opposed to work.

The Three MRA Methods

The three MRA methods to be linked with the information base available from the Altoona sample of the VDS are (1) Single Equation Models, (2) Commonality Analysis, and (3) Path Analysis. Alternatives (2) and (3) involve the use of structural equation models (Mood, 1971) which are based on a specifically defined set of regression equations. Each MRA technique is briefly described below.

Single equation model. This formulation represents a statistical model where all the treatment and covariate (independent) variables in the equation appear in a single ordinary least-square equation. Its form is:

$$Y = b(0) + b(1)X(1) + b(2)X(2) + b(3)X(3) + b(4)X(4) + b(5)X(5) + b(6)X(6) + e$$

where

Y = student's income in dollars per week one year after graduation from high school.

X(1) = student's IQ (GATB G).

X(2) = student's socioeconomic status (Father's occupational and educational level).

X(3) = student's prior achievement (GPA for grades 7, 8, and 9).

X(4) = student's curriculum (1 = vocational; zero otherwise).

X(5) = student's achievement (GPA for grades 10, 11, and 12).

X(6) = student's initial income in dollars per week following high school graduation.

e = the error component

b(i) = the least-squares weighting coefficient for variable i.

b(0) = the intercept term.

Variables X(1) and X(6) and Y were taken directly from measures offered in the Altoona sample of the VSD project, and variables X(2), X(3), X(4) and X(5) were constructed from additional measures in the same data base. These variables are the same for all the three alternative MRA approaches.

Commonality analysis. While primitive single equation models often produce useful insights, contemporary mathematical representations of educational systems are more likely to take the form of a system of equations. One such system is the set of structural equations offered in commonality analysis (Cooley and Lohnes, 1976). For our seven variable system (six predictors and a single criterion), commonality analysis provides 63 structural equations and an identical number of variance components. The 63 structural equations can be summarized as follows:

Y on X(I)	(6/1) = 6
Y on X(I) and X(J)	(6/2) = 15
Y on X(I), X(J) and X(K)	(6/3) = 20
Y on X(I), X(J), X(K) and X(L)	(6/4) = 15
Y on X(I), X(J), X(K), X(L) and X(M)	(6/5) = 6
Y on X(1) to X(6)	(6/6) = 1

Here the symbol (6/a) represents the standard probability notations for the (a) logical unique combinations in a set of six elements. Rules for the decomposition

of explained variance into six unique and 57 shared components were derived using the general decomposition algorithm provided in Mood (1969).

Path analysis. A second contemporary mathematical representation of educational systems which appears in evaluation research and longitudinal studies of career development is path analysis. For the seven variable system, the initial model specification is given in Figure 1. Variables X(1) and X(6) are identical to those elaborated for the single equation model. Variable X(7) is Y from the variable legend provided with the single ordinary least-squares equation. The specification of the actual structural equations that follow from the causal diagram depicted in Figure 1, the test of the adequacy of this causal framework, and the estimation of the direct and indirect effects in the system follow the recursive modeling procedures given in Namboodiri, Carter and Blalock (1975).

Results

The results of the analyses using each of the three MRA methods are presented separately for each method. The relevant information is provided in table form followed by brief answers to the two evaluation questions posed previously.

The Single Equation Model

Table 1 presents the intercorrelation matrix among all seven variables included in the model. As can be seen from the table, only initial income (X6) was significantly related to the criterion variable, final income (X7). Table 2 presents the full model MRA with all six independent variables included. As can be seen from Table 2, the coefficient of determination (R^2) is equal to .15; however, only the initial income variable (X6) is a significant unique contributor to final income (X7).

The first evaluation question examines the relationship that exists between the curriculum and final incomes of students in the particular sample. It reads

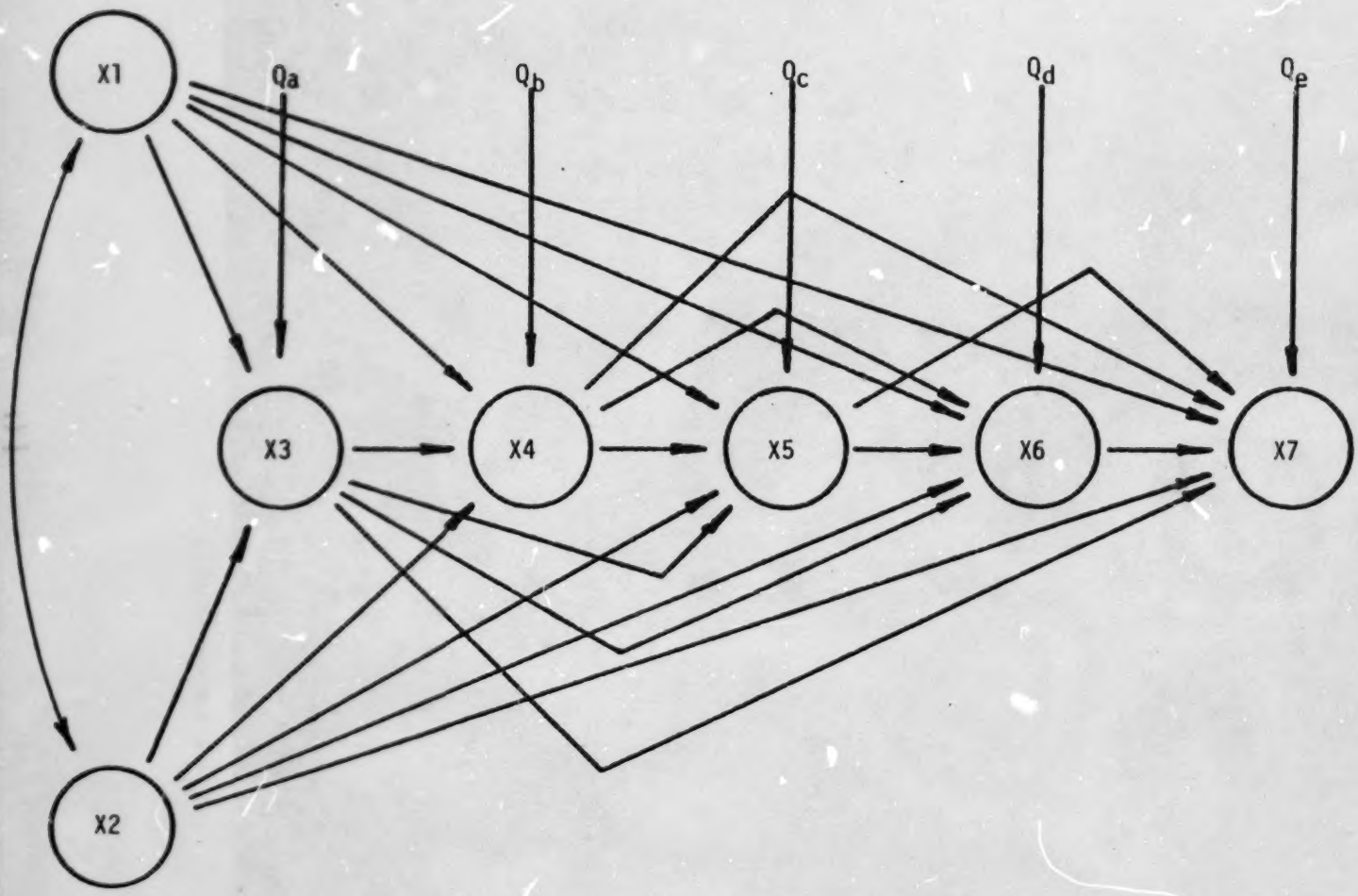

Figure 1. Initial Path Analysis Model.

Table 1. Zero-Order Correlations Means and Standard Deviations for the Variables in the Total Sample (N = 348).

Variables	X(1)	X(2)	X(3)	X(4)	X(5)	X(6)	X(7)
X(1)	1.0000	0.1288	0.4757	-0.2111	0.3470	-0.1063	-0.0539
X(2)		1.0000	0.0598	-0.1640	-0.0400	-0.0453	-0.0287
X(3)			1.0000	-0.2702	0.6194	-0.0277	-0.0108
X(4)				1.0000	-0.0410	0.0702	0.0354
X(5)					1.0000	-0.0567	-0.0368
X(6)						1.0000	0.3857
X(7)							1.0000
Means							
Voc. Ed.	90.82	32.62	310.09	1.0	323.70	82.94	95.49
Acad.	95.57	35.25	340.87	0.0	328.63	81.18	92.16
Total	92.61	33.56	321.57	0.63	325.51	82.27	94.28
Standard Deviation							
Voc. Ed.	11.14	7.76	52.83	0.0	55.59	47.03	47.73
Acad.	9.93	7.35	53.87	0.0	62.26	40.93	40.82
Total	10.93	7.71	55.18	0.48	58.09	44.75	45.31

Variables

X(1) = Intelligence (IQ) scores from GATB-G.
X(2) = Socioeconomic status index value.
X(3) = Grade point average for grades 7, 8 and 9.
X(4) = Curriculum choice (1 if vocational; 0 otherwise).
X(5) = Grade point average for grades 10, 11 and 12.
X(6) = Initial income following graduation.
X(7) = Weekly income one year following graduation.

$r \geq .104$ significant at .05

$r \geq .137$ significant at .01

$r \geq .174$ significant at .001

Table 2. Regression Analysis Between the Six Independent Variables in the Full Model and the Dependent Variable (N = 348).

Variables #	Name	Beta	F-Value	Alpha Value ($p \leq \alpha$)
1	IQ	0.01310	0.051	N.S.
2	SES	0.00851	0.028	N.S.
3	Prior achievement	-0.02489	0.124	N.S.
4	Curriculum	0.01008	0.035	N.S.
5	Post achievement	0.02523	0.151	N.S.
6	Initial income	0.38247	57.575	.001

Coefficient of Determination $R^2 = 0.14949$

Overall F-ratio $\frac{MSR}{MSE} = 9.98906$

as follows: Does participation in vocational education make a difference in weekly income in dollars one year after graduation? In response, the estimates provided in this single equation model clearly indicate that participation in vocational education does not have a significant statistical relationship with students' earnings one year after graduation.

This result is in contradiction with the results of such studies as Hu, Lee, and Stromsdorfer (1969), Conroy and Diamond (1976), and Conroy (1979). One possible explanation for this contradiction might be that there is something peculiar about this sample. Another might be that errors in measurement of the variables entered in the equation could account for differences. From a more theoretical point of view, it might also be advanced that major differences in findings are due explicitly to specification errors in one or more of the actual models compared here. However, the results provide no evidence that the vocational students are earning any less than the nonvocational students from the sample who also entered the labor force upon completion of high school.

The second evaluation question investigates the effects of other intervening variables on the earnings of the students in the labor market. It reads as follows: What are the influences of the different intervening variables on the external program outcome which is the weekly income in dollars one year after graduation? In response, consideration of the B's in this single equation model indicate that the only statistically significant relationship exists between the initial income and final income (B = .38247). This B(6) value suggests that a one standard deviation change in initial income results in a .38 standard deviation change in final income. The unstandardized regression coefficient for this variable is b = .39. This suggests that a one-dollar increase in the initial income will result in a .39 dollar increase in the final income. Thus the initial income appears to be the only intervening variable which has a significant

association with the outcome variable. Hence, the model offered here clearly suggests that the final income of the students will depend on where and at precisely what income rate the students started in the job market.

Commonality Analysis

Commonality analysis requires partitioning the total variance into its unique and shared components. Using six predictor variables, the partitioning would result in 63 separate structural equations. Following the suggestions of Cooley and Lohnes (1976), not all of the 63 possible variance components were calculated in order to reduce the resulting partitions to a manageable and realistically interpertable number. Thus, for the purpose of this study it was decided to calculate the variances unique to each variable, variances common to two variables at a time, and the remaining variance (balance) not included in the above. This procedure resulted in 22 different variances partitions being calculated.

The R^2 values for each of the 63 possible structural equations can be found in Table 3. The partitioning for the 22 sets of variables for which unique and shared variances were calculated are shown in Table 4. From examining the table, it can be seen that initial income (X6) uniquely accounts for 14.36 percent of the total of 14.88 percent of variance accounted for by X6 in conjunction with the other variables. All variables together account for only 14.95 percent of the variance in initial income.

The first evaluation question tries to establish the relationship that exists between the curriculum and final incomes of students in this particular sample. It reads as follows: Does participation in vocational education make a difference in weekly income in dollars one year after graduation? In response, the commonality analysis indicates that curriculum selection has no statistically significant relationship with final income. Moreover, its association with other predictors in the form of two-part and balance decompositions does not contribute significantly to the variance explained.

Table 3. R-Squared Values for the 63 Structural Equations

Notation
Predictor Variables are numbered 1, 2, 3, 4, 5 and 6.

Variable 1: IQ
Variable 2: Socioeconomic status
Variable 3: Prior Achievement
Variable 4: Curriculum (vocational vs. nonvocational)
Variable 5: Post Achievement
Variable 6: Initial income

V(J,K,M) is the criterion variance explained or the criterion redundancy for a multiple regression model using predictor variables J, K, and M.

V(1)	.0029	V(2,3,5)	.0024
V(2)	.0008	V(2,3,6)	.1489
V(3)	.0001	V(2,4,5)	.0030
V(4)	.0013	V(2,4,6)	.1489
V(5)	.0014	V(2,5,6)	.1491
V(6)	.1488	V(3,4,5)	.0033
V(1,2)	.0034	V(3,4,6)	.1488
V(1,3)	.0032	V(3,5,6)	.1491
V(1,4)	.0035	V(4,5,6)	.1491
V(1,5)	.0033	V(1,2,3,4)	.0043
V(1,6)	.1489	V(1,2,3,5)	.0049
V(2,3)	.0009	V(1,2,3,6)	.1491
V(2,4)	.0018	V(1,2,4,5)	.0043
V(2,5)	.0021	V(1,2,4,6)	.1491
V(2,6)	.1489	V(1,2,5,6)	.1492
V(3,4)	.0013	V(1,3,4,5)	.0056
V(3,5)	.0016	V(1,3,4,6)	.1490
V(3,6)	.1488	V(1,3,5,6)	.1493
V(4,5)	.0025	V(1,4,5,6)	.1491
V(4,6)	.1488	V(2,3,4,5)	.0037
V(5,6)	.1490	V(2,3,4,6)	.1489
V(1,2,3)	.0037	V(2,3,5,6)	.1493
V(1,2,4)	.0039	V(2,4,5,6)	.1491
V(1,2,5)	.0038	V(3,4,5,6)	.1493
V(1,2,6)	.1490	V(1,2,3,4,5)	.0059
V(1,3,4)	.0040	V(1,2,3,4,6)	.1491
V(1,3,5)	.0044	V(1,2,3,5,6)	.1494
V(1,3,6)	.1490	V(1,2,4,5,6)	.1492
V(1,4,5)	.0039	V(1,3,4,5,6)	.1494
V(1,4,6)	.1490	V(2,3,4,5,6)	.1494
V(1,5,6)	.1491	V(1,2,3,4,5,6)	.1495
V(2,3,4)	.0018		

Table 4. A Commonality Analysis Including All the Independent Variables

Variance profiles	% of variance associated with						Cumulative
	X1	X2	X3	X4	X5	X6	
Unique effects							
X1	.01						.01
X2		.01					.02
X3			.03				.05
X4				.01			.06
X5					.04		.10
X6						14.36	14.46
Unique total	.01	.01	.03	.01	.04	14.36	14.46
Two part							
X1 and X2	.00	.00					.00
X1 and X3	.00		.00				.00
X1 and X4	.00			.00			.00
X1 and X5	.01				.01		.01
X1 and X6	.21					.21	.22
X2 and X3		.00	.00				.22
X2 and X4		.00		.00			.22
X2 and X5		.00			.00		.22
X2 and X6		.02				.02	.24
X3 and X4			.01	.01			.25
X3 and X5			.03		.03		.28
X3 and X6			.13		.13		.41
X4 and X5				.01	.01		.42
X4 and X6				.09		.09	.51
X5 and X6					.12	.12	.63
Two part total	.22	.02	.17	.11	.30	.44	.63
Balances	.06	.05	-.19	.01	.07	.08	.00
Totals	.29	.08	.01	13	.14	14 88	14.35

Note: Certain partition summaries will vary slightly from initial R^2 values due to rounding errors and suppressor variables. Totals for each variable are the R^2 values for the criterion regressed on that variable exclusively. The totals entry in the last column is the R^2 value for the criterion regressed on X(1) through X(6).

The second evaluation question examines the effects of other intervening variables on the earnings of the students in the labor market. It reads as follows: What are the influences of the different intervening variables on the external program outcome which is the weekly income in dollars one year after graduation? In response, the commonality analysis indicates that initial income is the best predictor of final income. Its unique plus-shared variance is 14.88 percent. No other intervening variable makes an important contribution to final income.

In summary, the results of the commonality analysis suggest two findings. First, nonvocational and vocational students do not appear to be significantly different in terms of their earning power in the labor market, when the earnings measure is taken one year following the data of their high school graduation. Second, the best and only significant predictor of final income is initial income.

Path Analysis

The causal model to be tested in this section of the study is depicted in Figure 2. In this model, it is assumed that the students' final income is affected by their initial income. This factor is in turn affected by students' post achievement, which itself is affected by curriculum selection. Selection of the curriculum is believed to be influenced by students' prior achievement which is influenced by IQ and socioeconomic status.

There are two exogenous and five endogenous variables in this model. All but the first two variables, IQ (X1) and socioeconomics status (X2), are considered to be endogenous, and as such to be determined by variables included in the model as well as by residual variables. The residual variables (Q) represents the effects of all other variables not specified in the model. Following standard path analysis constraints, it is assumed that a residual variable is uncorrelated with variables that determine the endogenous variables. Moreover, it is also assumed that no two residual variables are correlated.

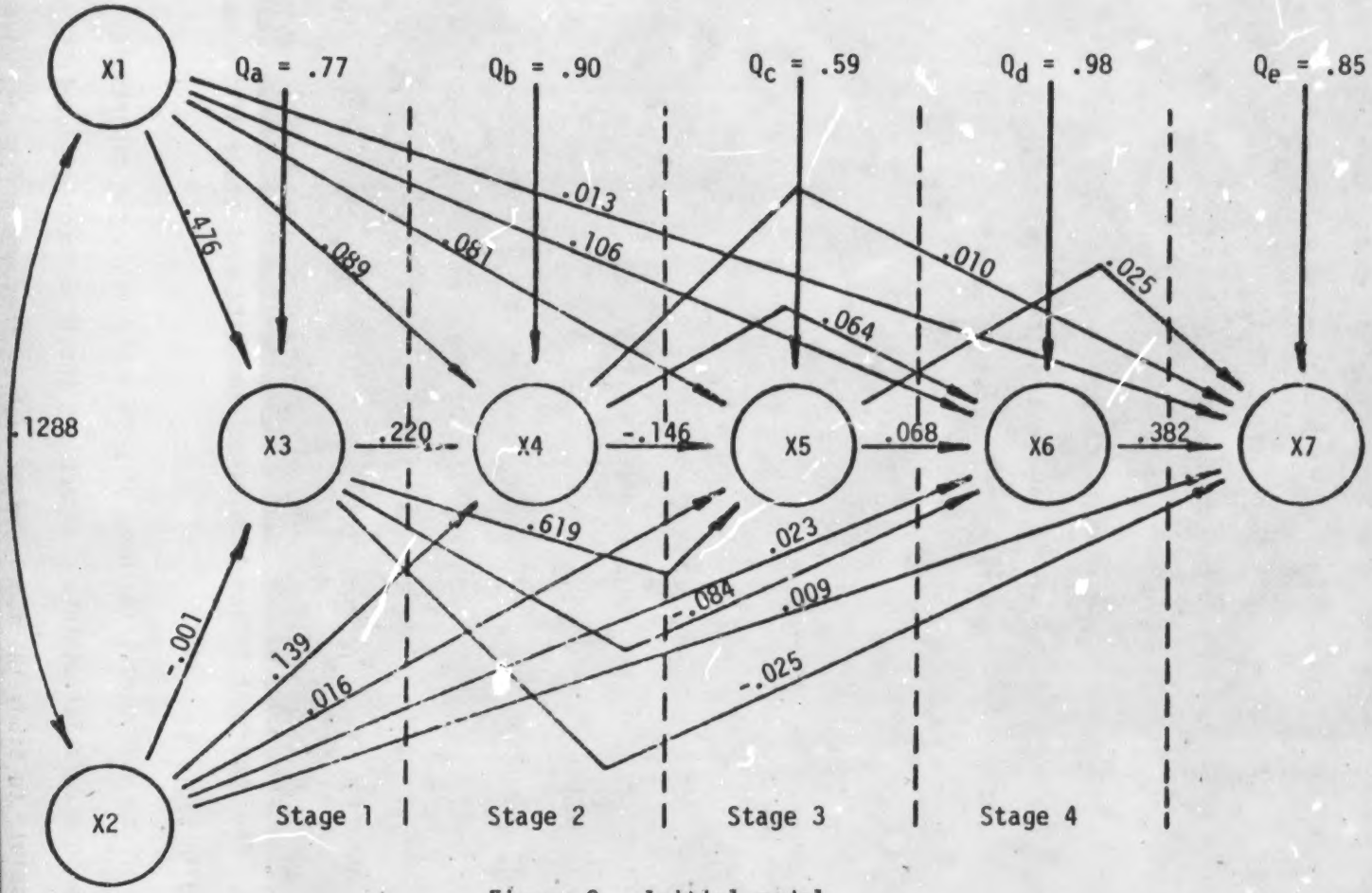

Figure 2. Initial model.

The relationship between the exogenous variables is shown with a curved double headed arrow. The effects of exogenous variables on endogenous variables and endogenous variables on other endogenous variables are shown by a straight arrow. The values entered on the straight arrows are the path coefficients. The path coefficients are the standardized Beta weights resulting from regressing a criterion variable on its specified predictor set.

The path theorem provides the basis for testing the mathematical adequacy of a derived model. The formula for this test is as follows:

$$r_{IJ} = \sum_{q} P_{Iq} r_{qJ}$$

where:

r = correlation coefficient.

P = path coefficient.

I - the number of the dependent variables.

J = the number of the independent variables.

q = an index of all numbers between J and I, including J.

The significance of a path coefficient is tested using the standard test of statistical significance for Beta. Paths are retained in the model if either they are statistically significant or if they serve some strong theoretical reason for existance (see the discussion of "Theory Trimming Approaches" in Heise, 1969). Following this procedure, a modified path model was calculated and appears in Figure 3. The important information associated with each stage of the model is presented in Table 5.

One of the most useful features of path analysis is the opportunity it provides to decompose a correlation into a direct and total indirect effect (TIE). Thus, it is possible to study the magnitude of each of the components and, more important, examine the role they play in the model. To calculate the total indirect effect

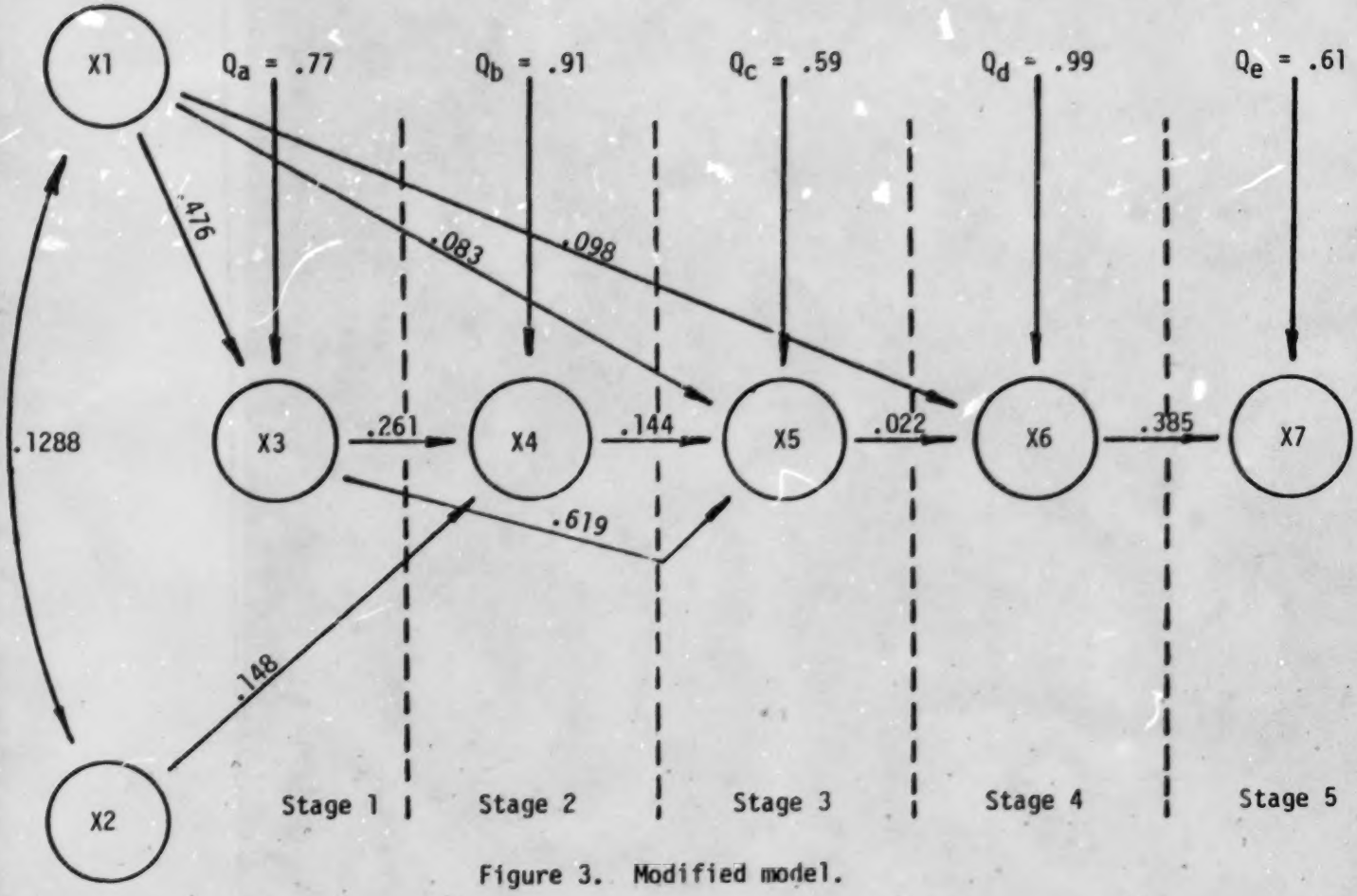

Figure 3. Modified model.

Table 5. Standardized Partial Coefficients (Path Coefficients) for the Modified Model (N = 348).

Dependent Variable	Independent Variables	Standardized Partial Regression Coefficients	Standard Error	Significance Level
Stage 1				
Prior Achievement	IQ	0.476	0.047	.01
				R^2 = .23
Stage 2				
Curriculum	Socioeconomic status	0.148	0.051	.01
	Prior achievement	0.261	0.051	.01
				R^2 = .09
Stage 3				
Post Achievement	IQ	0.083	0.047	.05
	Prior achievement	0.619	0.048	.01
	Curriculum	-0.144	0.043	.01
				R^2 = .41
Stage 4				
Initial Income	IQ	0.098	0.057	N.S.
	Post achievement	0.022	0.057	N.S.
				R^2 = .01
Stage 5				
Final Income	Initial Income	0.385	0.049	.01
				R^2 = .15

of a variable the following formula is used:

$$TIE(IJ) = r(IJ) - P(IJ)$$

These total indirect and direct effects are presented in Table 6.

The results of this part of the study are first presented as they pertain to the different stages. Later thay are presented as they pertain to the two evaluation questions.

In the first stage, prior achievement is regressed on IQ and socioeconomic status. This results in a statistically nonsignificant path for socioeconomic status. Thus socioeconomic status is deleted and achievement alone is regressed on IQ. The R^2 for this equation is .23, and the F-ratio is significant at the .01 level. Thus, the total effect of IQ on prior achievement is .48 and all of it is direct.

In the second stage, curriculum is regressed on IQ, socioeconomic status, and prior achievement. The path coefficient for IQ is not significant. Accordingly, IQ is dropped and curriculum is regressed on socioeconomic status and prior achievement. These results indicate that both socioeconomic status and prior achievement affect curriculum selection. The R^2 for this equation is .09 and it is significant at the .01 level. Both of these variables affect curriculum selection in direct and indirect ways, but most of the influence is direct for both of the variables.

In the third stage after the deletion of insignificant paths, only IQ, prior achievement, and curriculum are left. The R^2 for this model is .41. Prior achievement's influence on post achievement is direct, and the magnitude of this influence is .62. The influence of IQ on post achievement is almost entirely indirect, with the total effect of curriculum being -.04. For curriculum, the direct effect is -.14.

In stage four, IQ and post achievement have significant paths, and they are the only variables maintained in the modified path model. The R^2 for this model

Table 6. Contribution of Variable to Total Effects in Each Stage (N = 348).

Variable	Dependent Variable	Direct Effects	Total Indirect Effects	Total Effects
Stage 1				
Prior Achievement	IQ	.48	0.00	.48
Stage 2				
Curriculum	Socioeconomic status	.15	.01	.16
	Prior achievement	.26	.01	.27
Stage 3				
Post Achievement	IQ	.08	.29	.37
	Prior achievement	.62	.0	.62
	Curriculum	-.14	.10	-.04
Stage 4				
Initial Income	IQ	.10	-.21	-.11
	Post achievement	.02	-.07	-.05
Stage 5				
Final Income	Initial Income	.39	.00	.39

is .01. The direct effects for the variables in this stage are .10 for IQ and .02 for post achievement.

In stage five, the only significant path is between initial income and final income. Thus final income is regressed only on initial income and an R^2 of .39 is obtained. This indicates that final income is heavily influenced by initial income. Since this is the only predictor variable in the model at this point, its influence is entirely direct. Thus, it has a magnitude of .39.

Examinations of the results with respect to the two evaluation questions reveal the following:

The first evaluation question tries to establish the relationship that exists between the curriculum and final incomes of students in this particular sample. It reads as follows: Does participation in vocational education make a difference in weekly income in dollars one year after graduation? In response, the path analysis results suggest that vocational education does not affect income in the labor markets, but it affects post achievement which in turn affects initial income. In this modeling framework, it is also significant to notice that curriculum selection is affected by socioeconomic status and prior achievement.

The second evaluation question is trying to study the effects of other intervening variables on the earnings of the students in the labor market. It reads as follows: What are the influences of the different intervening variables on the external program outcome which is the weekly income in dollars one year after graduation? In response, the path analysis results suggest that there are no direct paths of influence from any of the predictor variables in the model except initial income. Hence, it can be said that only initial income affects a student's income measured one year following the completion of high school and the effects of the other intervening variables are on variables antecedent to the initial income. However, while variables preceding the initial income of students do

not directly affect income indicated by students a year following high school graduation, they influence other variables which in turn influence final income.

Discussion

The results of this study indicate that single equation linear regression analysis, commonality analysis and path analysis do not lead to different conclusions with different policy implications. These standard statistical models all reflect the same results regarding the effects of vocational education programs and the influences of other intervening variables considered in this model. However, in the light of this analysis, the following deserves mention. While the three MRA methods yield the same overall coefficient of determination (multiple R-squared values), they have differential information values in terms of the intermediate results they are likely to provide when a researcher follows the standard procedures suggested for routine applications of these models. Furthermore, if the data base used in this study had yielded effects for the vocational education program with significant relationships between and among the various intervening variables, the opportunities to find differences among the three approaches would have been much greater. In any case, the benefits of the three approaches need to be considered further.

Single equation models in linear regression analysis normally use either the unstandardized regression coefficients or the Beta weights to test the influence of each predictor variable. These regression weights merely indicate the effects of each variable on the criterion while controlling for the effects of others. Single equation regression analysis models do not require a researcher to offer any testing information regarding the causal ordering of the variables of interest. Moreover, tests of individual Beta weights are not independent tests.

Commonality analysis provides more information about the same set of predictor variables in terms of their unique and shared variance. This enables the researcher to determine which variables and/or what combination of them are likely to produce the desired results.

The most information is provided by the standardized procedures routinely employed in path analysis. Path models not only provide estimates for the direct and indirect effects of a variable on other variables in the system, but they also reflect the direct and indirect influence of all other antecedent variables. Moreover, path analysis permits one to specify critical exogenous variables in addition to essential treatment considerations and outcome measures which are collectively viewed as the set of endogenous variables.

In light on these factors, the use of path analysis models is highly recommended for mathematical modeling of longitudinal data bases in evaluation of vocational education programs.

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